U.S. ARMY COMBAT CAPABILITIES DEVELOPMENT COMMAND – ARMY RESEARCH LABORATORY

Time-Resolved Ballistic Testing

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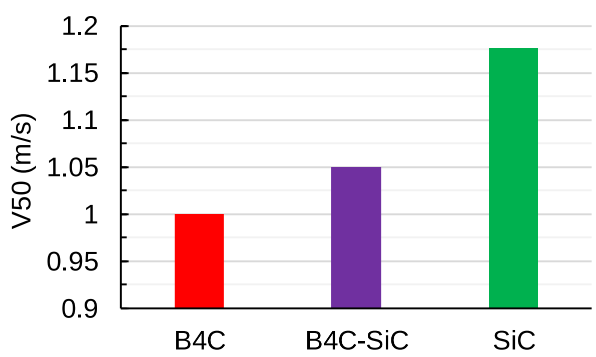
BACKGROUND

- Goal: **Enhanced Solider protection and effectiveness, enabling dominance of close-combat fight**
  – Next gen armor and projectiles
- **Materials processing & properties**
  – Properties and characteristics do not directly predict ballistic performance
  – Need ideal metrics to target efforts
- **Traditional ballistic testing**
  – Demonstrates outcomes and ranking with little insight into underlying physics
  – Expensive and requires bulk material
- **Computational design tools needed for design and analysis**
  – Need high-fidelity experimental input
- **Need insight into incipient failure mechanisms enabling rapid screening**
  → Time-resolved ballistic testing

Need to reduce hard armor weight

Source: © 2015 Filo LLC (image of soldier), U.S. Army and U.S. Marine Corps (images of individual equipment); data provided by Army and Marine Corps. | GAO-17-431

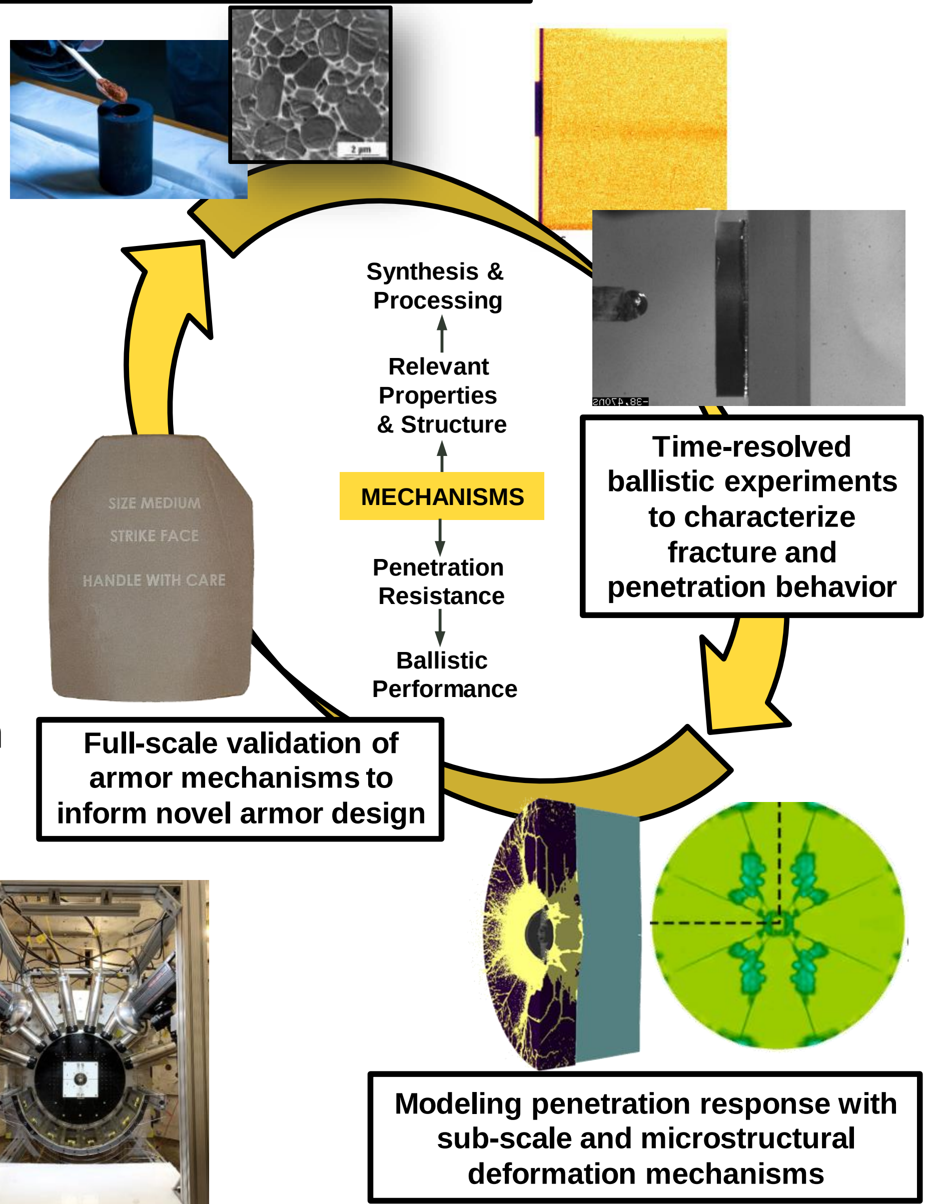
Ballistic Performance



MOTIVATION

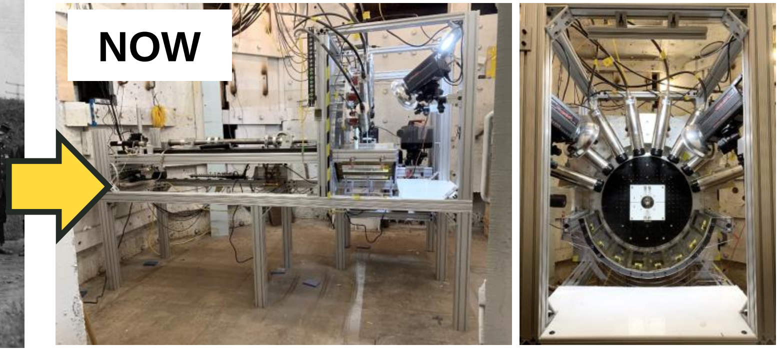
Novel processing science to enable unique materials, multi-scale structures and armor system design

- **Complex failure response**
  - Materials subjected to extreme dynamic loading
  - Impactor-target response non-linear in time
  - Severe gradients in the stress and strain
  - Multiple damage and failure modes
- **Need comprehensive framework:**
  - Insights into ballistic mechanisms
  - Rapid screening
    - Guidance to processing/characterization
    - Test emerging technologies at small-scale
  - Continuous feedback loop that connects through mechanisms informed by instrumented ballistics
- **Objective:**
  - Experimental-computational framework for accelerated engineering of future protection and projectile technologies



Advances in ballistic characterization

Demonstrating a bullet-proof vest, c. 1923.*Library of Congress*

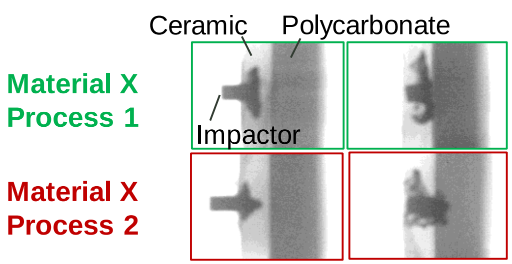


ACCELERATING DISCOVERY

- **ML + integrated testing to expedite and enable greater insights into ballistic phenomena**
  - Accelerate discovery and development cycle
  - Rapid screening of materials, technologies, and mechanisms
  - Move away from manual analysis (time-consuming, costly, and subjective)
  - Feed high-fidelity data into model development, validation, and optimization
- **Enable identification of transformative materials**
  - Aggregate resources (past work, experiments, computations) for predictions
  - ARL performs 1000s of tests per year with X-ray systems → data-rich environment
- **Provide mechanistic guidance to develop better materials and systems**
  - Leverage findings for enhanced lethality/protection

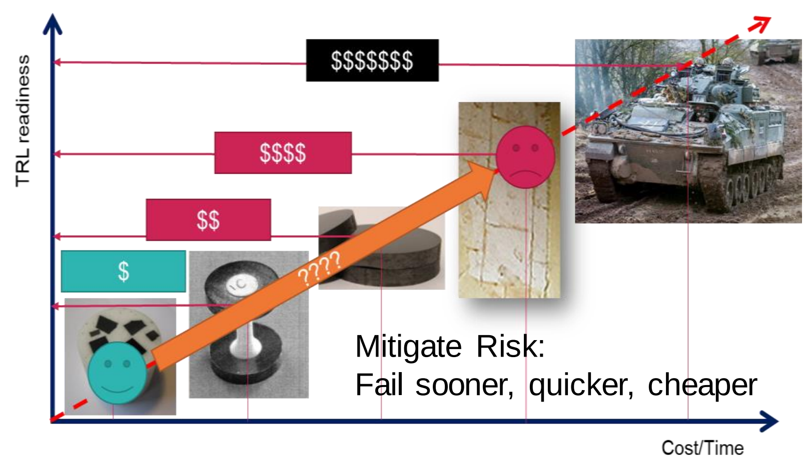
Screening novel processing schemes

10 tile 4” × 4” V_{50} = 2.30 kg powder = 460 powder batches
(+ capital for pressing large targets and machining)
→ 1 test with one set of parameters
HIDRA = 2.30 kg powder = 368 discs
→ latitude to test combinations of features, processes



Both powders look nearly identical with similar hardness

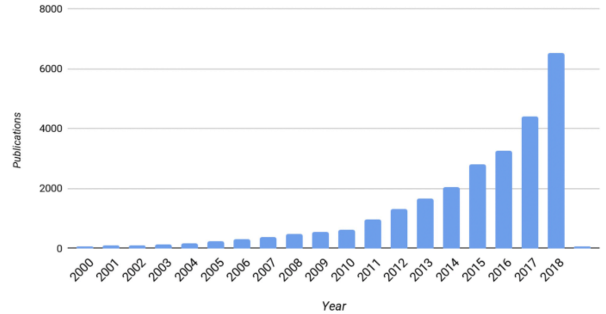
Non-ideal S&T Failure



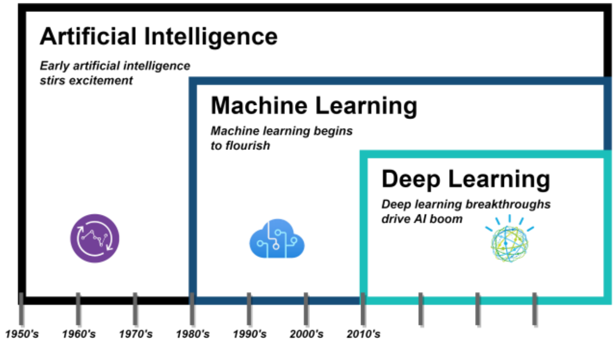
MACHINE LEARNING AS ENABLING TECHNOLOGY

- **Artificial Intelligence – Enables application to mimic human intelligence to predict, automate, and optimize tasks**
  - Machine Learning – Incorporates mathematical and statistic algorithms designed to allow application to “learn” from data
    - Neural Networks – Mimic operation of neurons in human brain for computation and comprised of layers of nodes
      - Deep Learning – Use neural net with more than 3 layers (incl. input/output layer)
- **Automated processing of multi-modal time-resolved ballistic data**
  - Based on methodology developed by Schuster (Python-based open-source code using Jupyter Notebooks)
  - Current code developed during 2020 pandemic shutdown
- **Distributable framework**
  - Select experiments can be shared collaboratively
  - Allows for personal or cloud-based computing
- **High-quality data in non-ideal environments**
  - ***Production scale testing has the poorest image quality but is an opportunity to generate large data sets!***

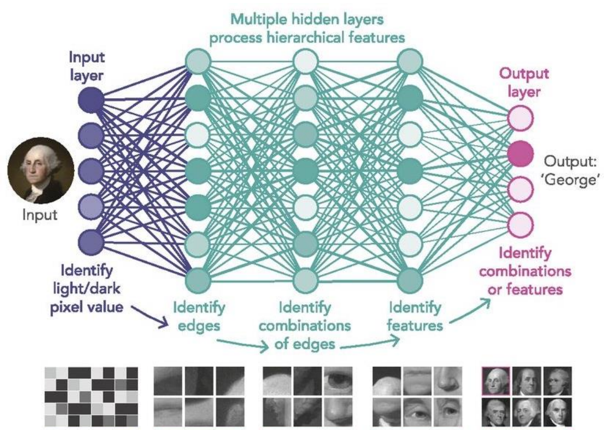
ML publications by year



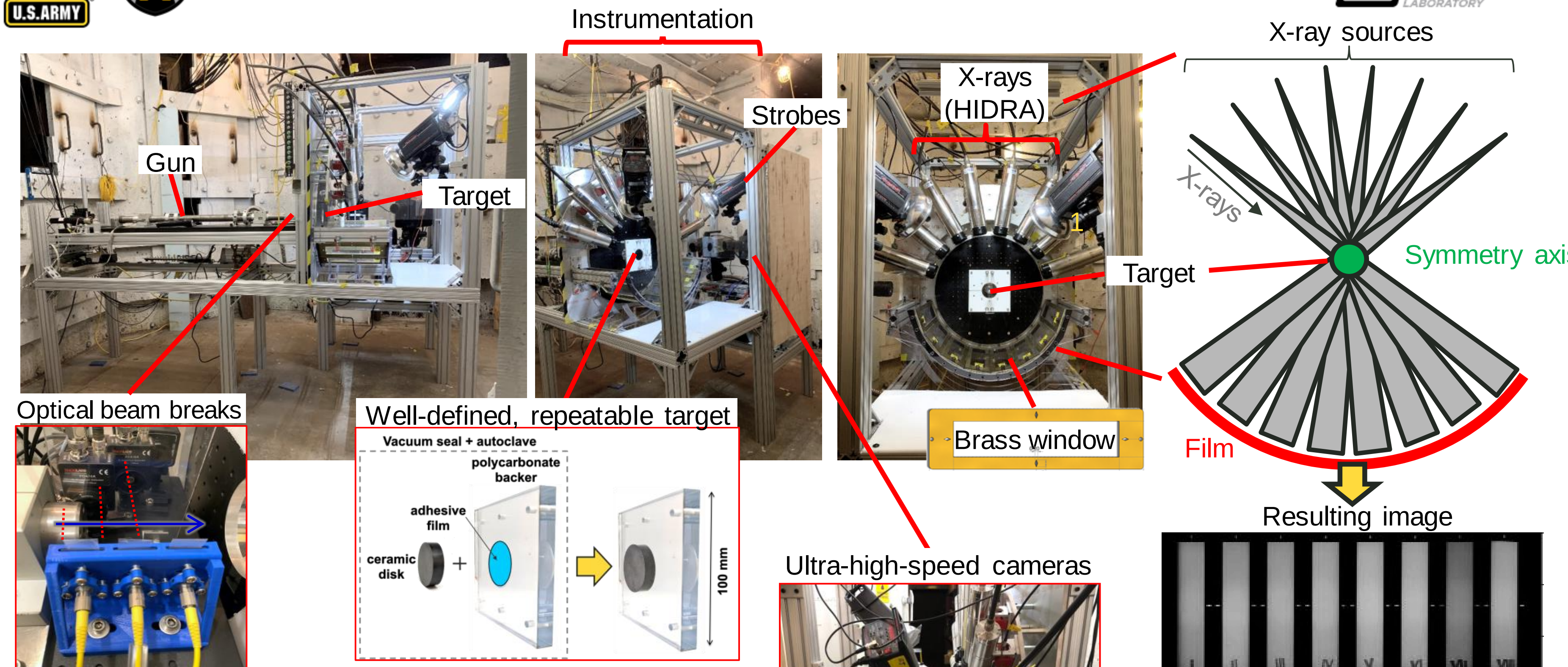
History of AI, ML, and DL

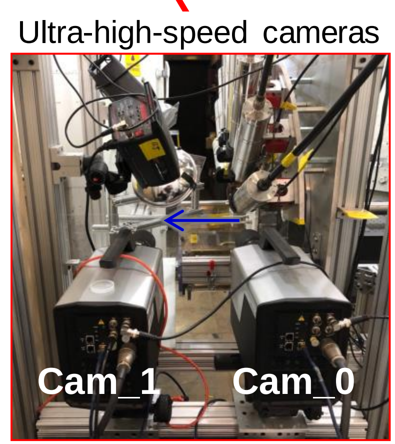


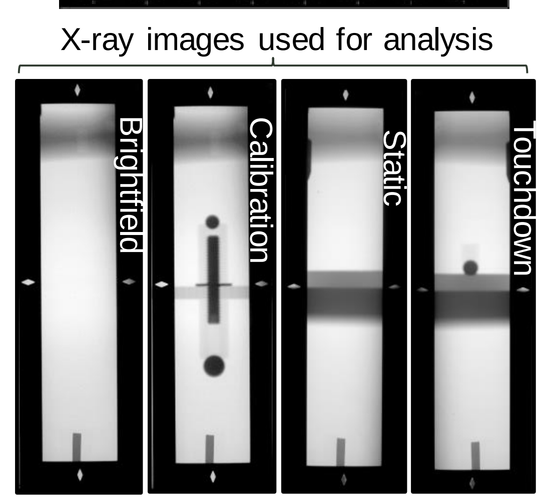
Deep Learning Neural Net



INTEGRATED BALLISTIC TESTING





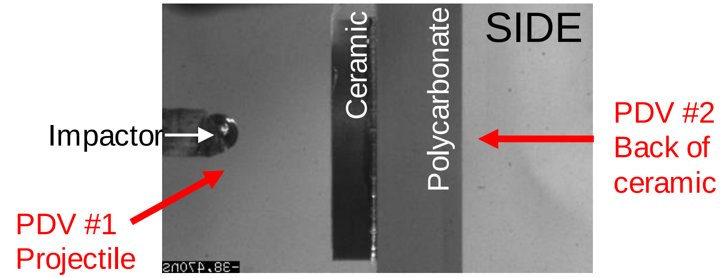


- *In situ* characterization of failure response using concurrent instrumentation
- Modular configuration enables wide variety of experimental investigations
- Precise, repeatable test design
- 0.25 to 0.50-cal barrels (0.3 – 2.5 km/s)
- Ultra-high-speed imaging (up to 10 Mfps)
- 8-channel Photonic Doppler Velocimetry (PDV) (measure 10s m/s to km/s with ns resolution)
- 8-channel 150 keV multi-flash X-ray (HIDRA)

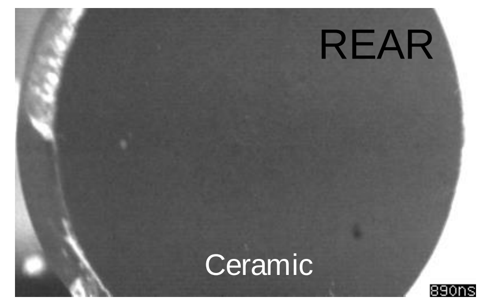
SEQUENCE OF EVENTS

- **Ballistic response**
  - PTI = less than 50 μs
  - Rear target cracking within 1 μs
  - PTI affects backer in <10 μs
- **PDV: projectile & back face velocity**
- **Cameras: fracture morphology**
- **X-rays with ML:**
  - Dwell time (no penetration)
  - Projectile length
  - Projectile consumption (rate of erosion)
  - Depth of penetration
  - Penetration velocity
  - Projectile-target interface shape

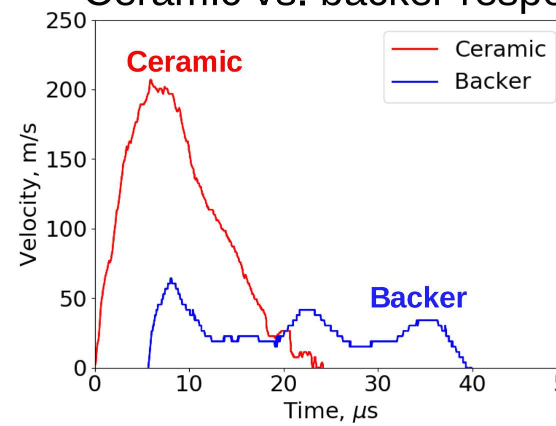
High-speed imaging
Total event ~50 us



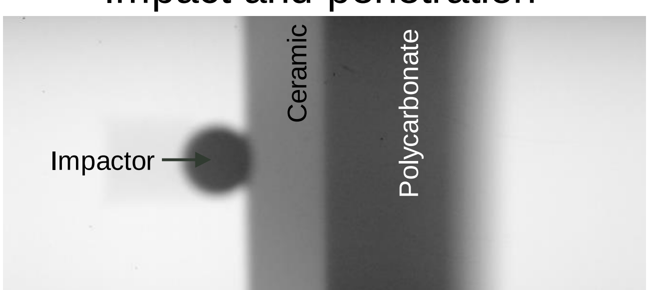
Ceramic fracture <10 μs



PDV
Ceramic vs. backer response



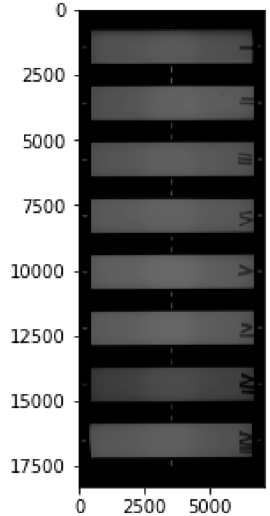
X-ray imaging
Impact and penetration

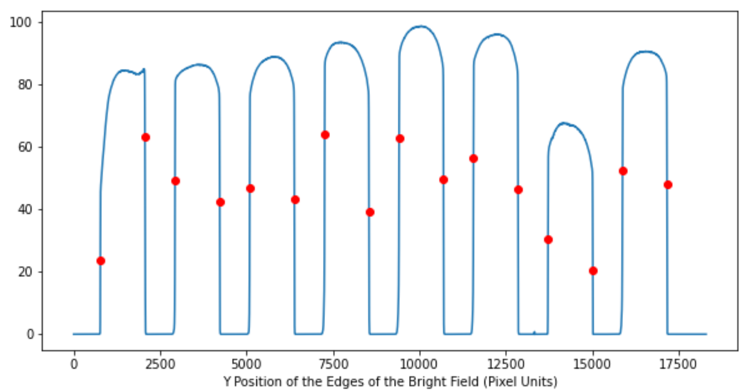


X-RAY ANALYSIS PART 1: COMPUTER VISION (CV)

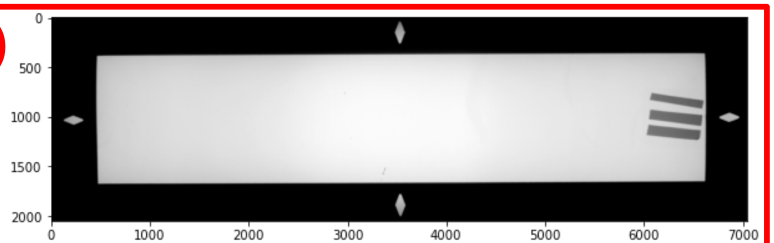
1. Identify individual frames
2. Crop/normalize contrast in each window
3. Register, align, and if warp frames into single frame of reference
4. Identify impact surface & create projectile contour using binarization
5. Measure penetration

(1)

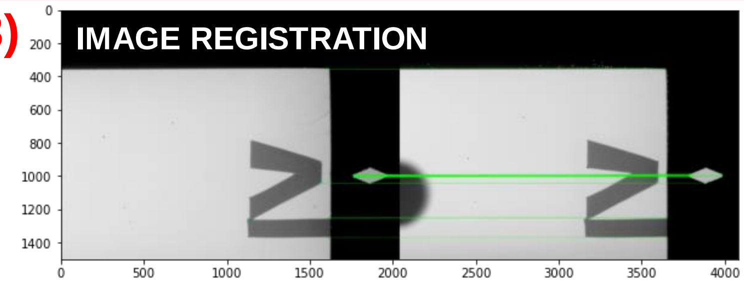


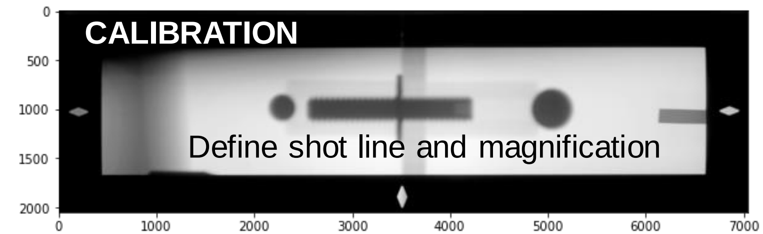


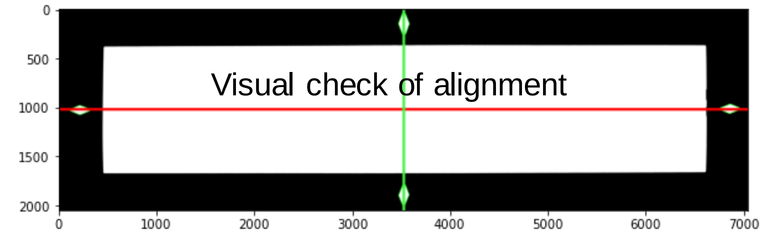
(2)



(3)

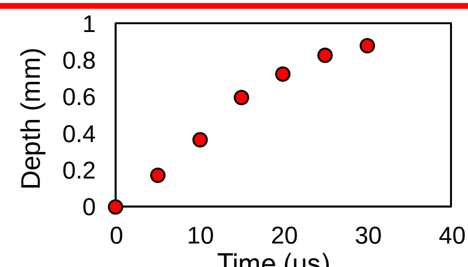






(4)

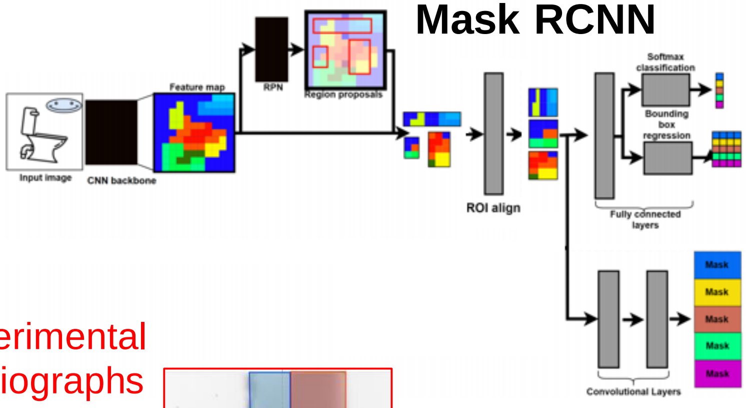
(5)



DEEP LEARNING APPLIED TO IMPACT EXPERIMENTS

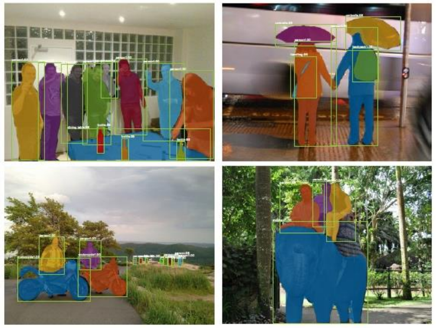
- Mask R-CNN = Deep neural network for Object Detection and Instance Segmentation <https://github.com/matterport/Mask_RCNN>

Mask RCNN



ML Training

Transfer Learning from Common Objects in Context (MS COCO)



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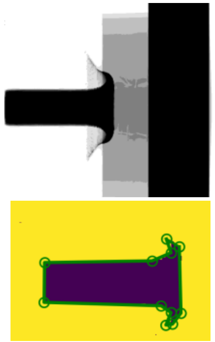
Synthetic Radiographs



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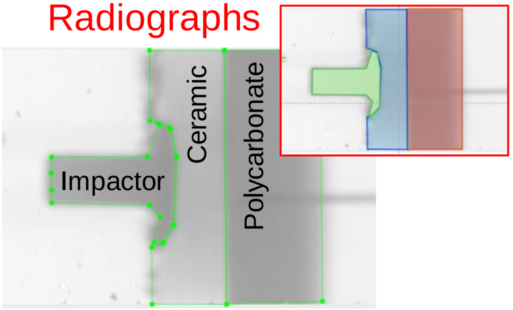
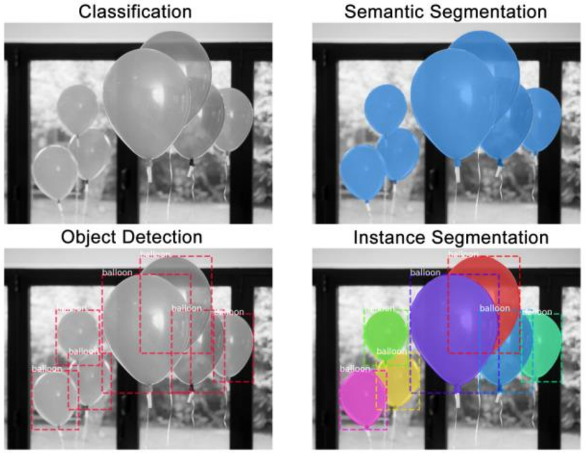
Experimental Radiographs



Object Recognition

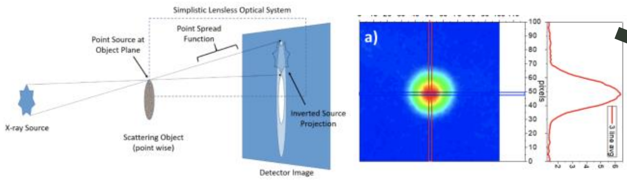


- Initially train model on limited dataset and preform automatic labelling to grow dataset
  - ML works best on large volumes of training data
- Re-train on large training deck for more robust segmentation
  - Pixel-wise mask for each object instance detected → more granular understanding of object(s) in the image

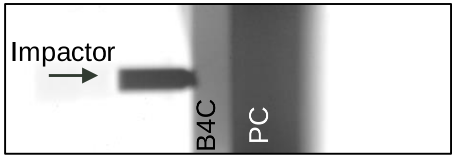
X-RAY ANALYSIS PART 2: MACHINE LEARNING (ML)

Image Restoration

PSF-Deconvolution→deblurring

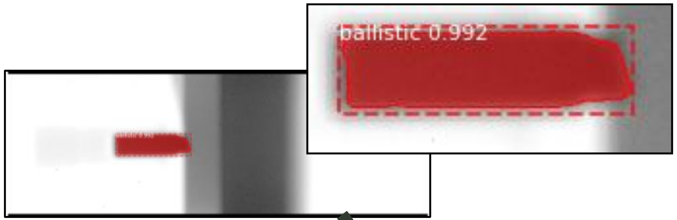


(2) Apply ML to pre-processed images



CV image processing (#1-3 previous slide)

(3) Instance Segmentation Using Machine Learning

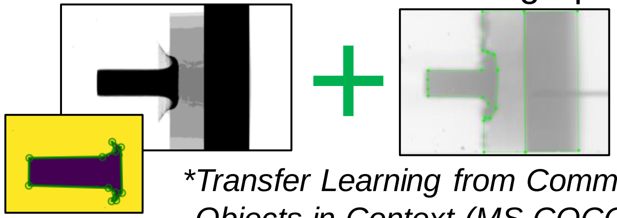


Mask R-CNN

(1) Train convolutional neural network

Synthetic Radiographs

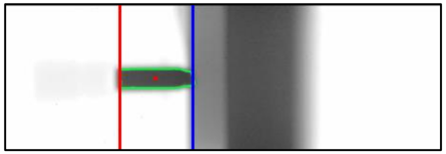
Experimental Radiographs



**Transfer Learning from Common Objects in Context (MS COCO)*

***Pre-trained with limited initial data set*

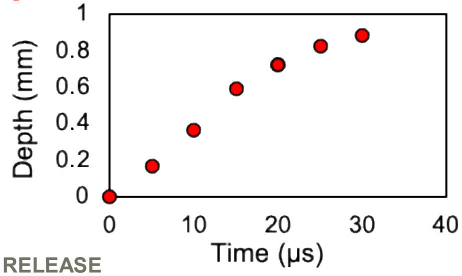
(4) Projectile Tracking



i. *Identify projectile contour*

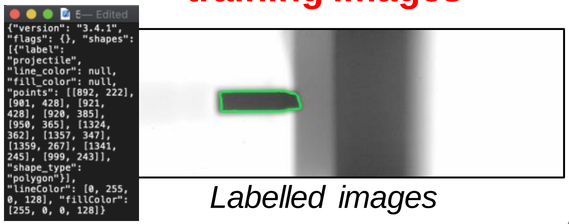
ii. *Extract projectile positions* (Nose/Tail/Centroid)

(5) Automated Data Reduction



(6) Update model with new training images

Image Annotations

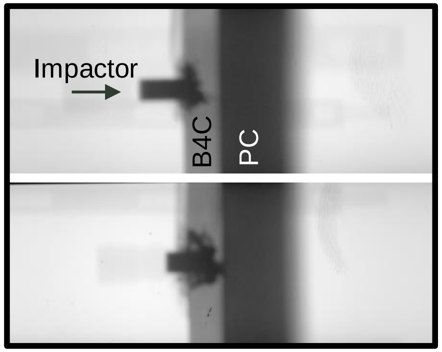


Labelled images

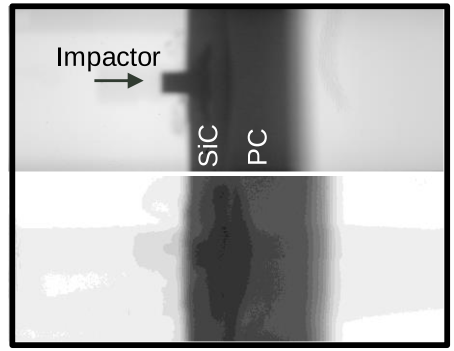
CV VS. ML – PROJECTILE DETECTION ACCURACY

X-ray images

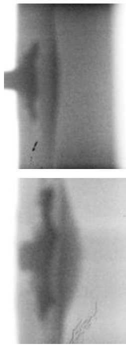
B4C



SiC



Enhanced Contrast



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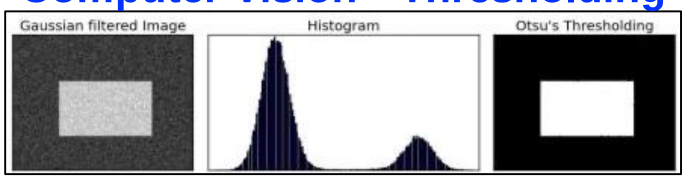
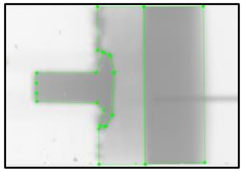
Computer Vision - Thresholding



OR….

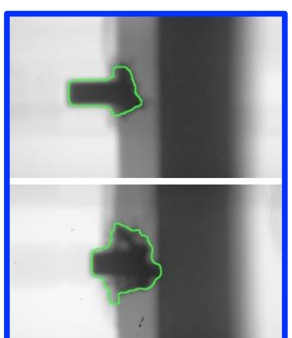
Machine Learning



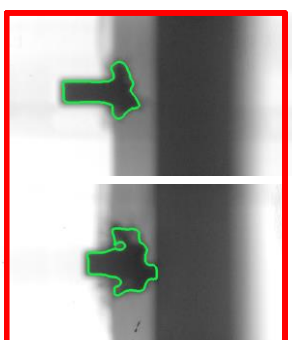
Conventional image segmentation methods often fail when there is poor contrast between the projectile and target – Need ML!

B4C

CV

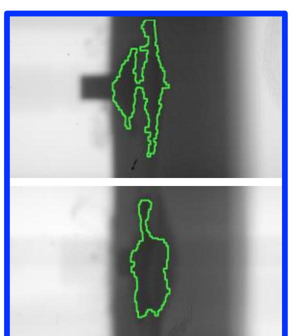


ML

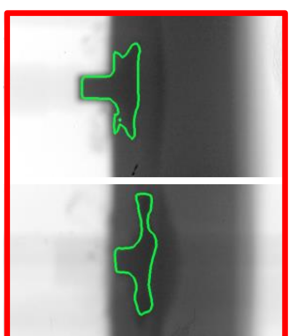


SiC

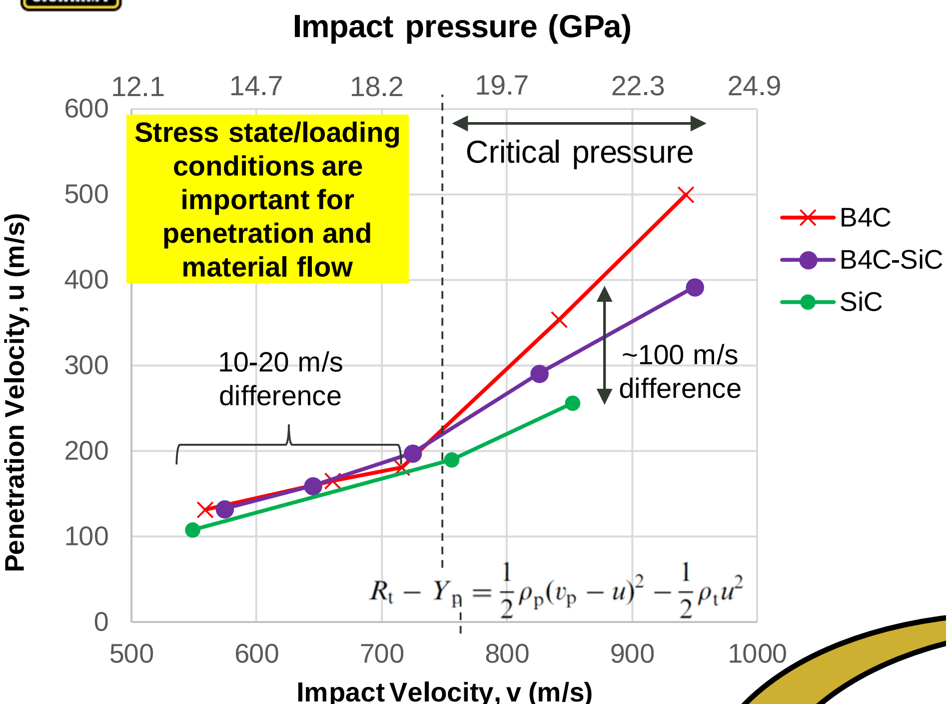
CV



ML



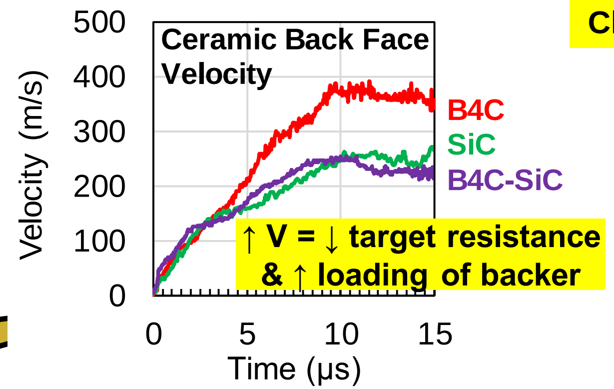
PENETRATION RESISTANCE



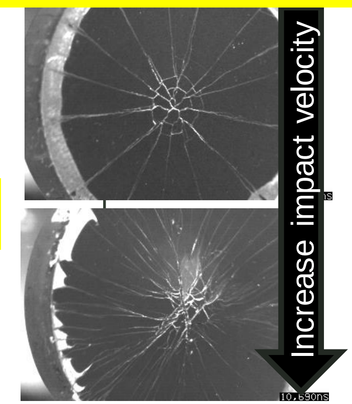
21 Gpa shock pressure

Material	Penetration Vel. (m/s)	Target Resistance (GPa)
B4C	360	1.7
B4C-SiC	310	2.1
SiC	257	2.6

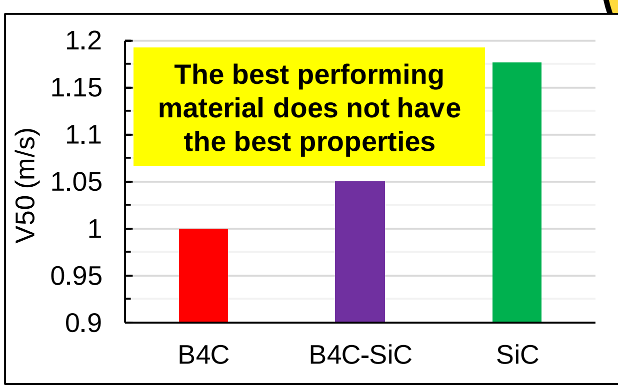
Decreasing penetration velocity = Increasing target resistance



Change in failure mode



Develop mechanics-based understanding of processing-performance relationship, e.g., critical stresses and stress states, associated deformation mechanisms, fragmentation and material "flow"



	Elastic Modulus (GPa)	Hardness (GPa)	Fracture Toughness (MPa•√m)	Comp. Strength (GPa)	Flexural Strength (MPa)	Fracture Mode
B4C	462	19.8	2.9	6.1	398	Trans
B4C-SiC	452	20.9	3.4	-	308	Trans
SiC	436	19.4	2.7	5.4	459	Trans

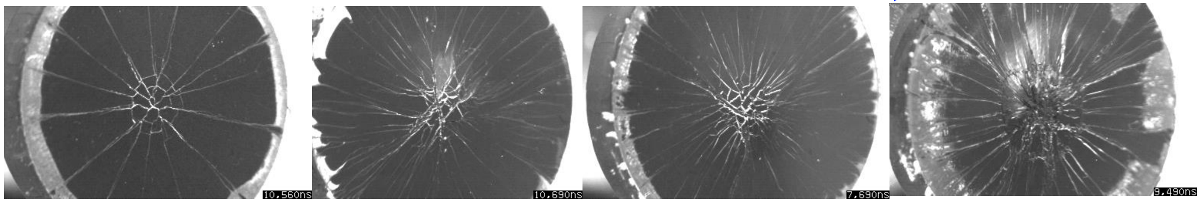
WRAP-UP & FUTURE DIRECTIONS

- Use state-of-the-art ML algorithms for *in situ* characterization of penetrator-target interactions
  - Direct comparisons between computational models and experiments
  - Capture and quantify mechanisms describing material failure
- HIDRA has addressed real-world terminal effects problems:
  - *Protection* – Screen commercial & research-grade materials to inform/guide processing
  - *Lethality* – Provide feedback on terminal effects for fielded projectiles (e.g. M855A1)
- **Future**: Apply ML to production-scale testing in ARL small-cal ranges where HIDRA systems are fielded

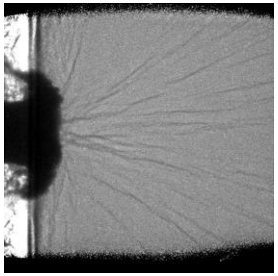
- **Future:**

Increasing Impact Velocity

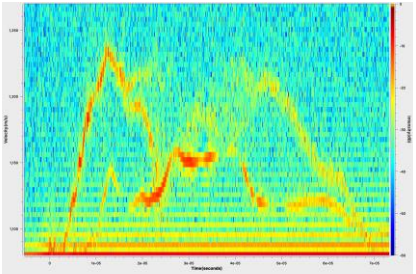
High-Speed Optical Imaging



Propagation-Based Phase Contrast Imaging



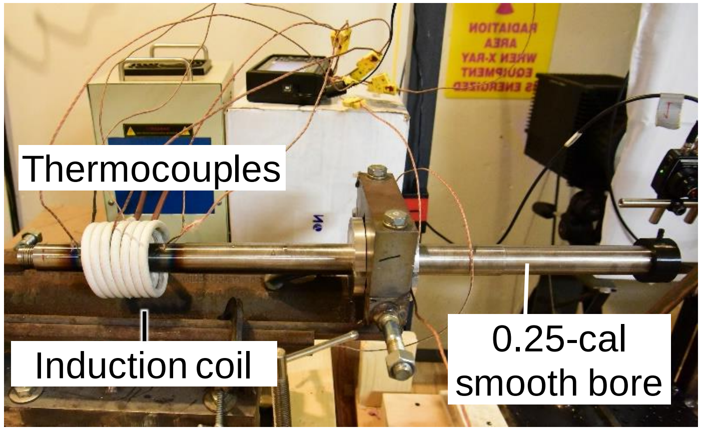
Velocimetry

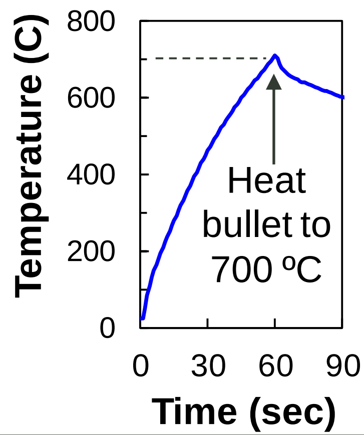


RAPID MATERIAL SCREENING OF WARHEAD MATERIALS

DEVCOM ARMY RESEARCH LABORATORY

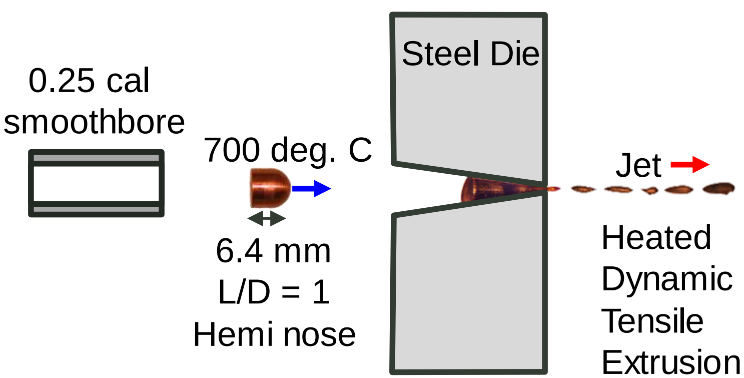
Heated Powder Gun



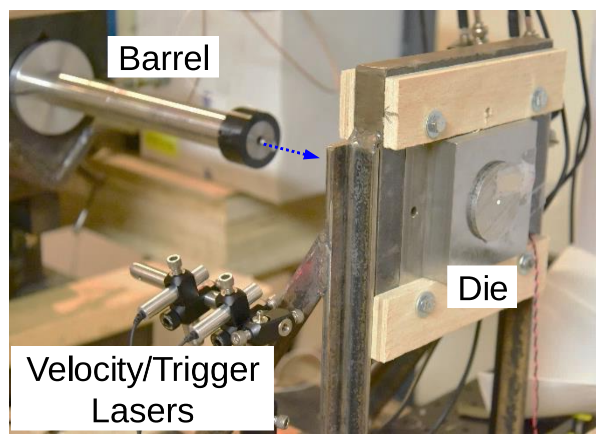


- 0.25-cal smooth bore powder gun
- Induction coil heats bullet
- Projectile fired into extrusion die
- Projectile subjected to extreme tensile elongation and jetting
- High-speed cameras capture jet formation

Schematic of Setup

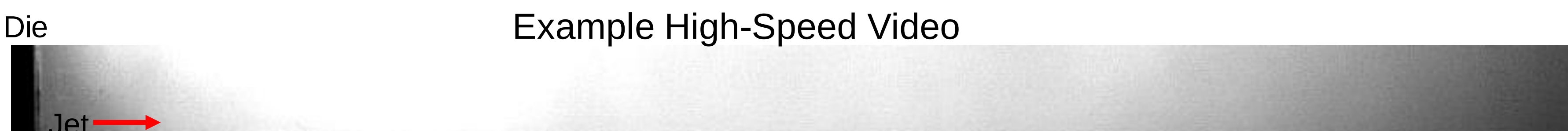


Dynamic Tensile Extrusion



High-Speed Imaging

Example High-Speed Video



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ARL Contributors:

Physics of Soldier Protection ERP: Andy Tonge, Pat Gillich, Chris Hoppel

Terminal Effects

- *Lethal Mechanisms*: Nicholas Lorenzo, Debjoy Mallick, Lee Magness, Tyler Ehlers
- *Impact Physics*: *Rich Becker,* Brian Leavy, John Clayton

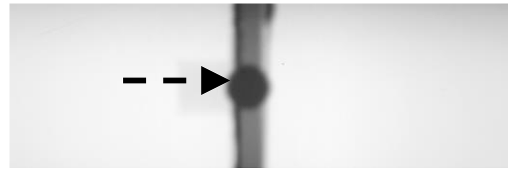
Sciences of Extreme Materials

- *Ceramics and Transparent Materials*: Jim Campbell, Anthony DiGiovanni, Jerry Lasalvia, Kris Behler
- *Composite and Hybrid Materials* : Doug Harris
- *Materials Response and Design*: Jessica Sun, Tim Walter

CV VS. ML– POSITION MEASUREMENT ACCURACY

X-ray images

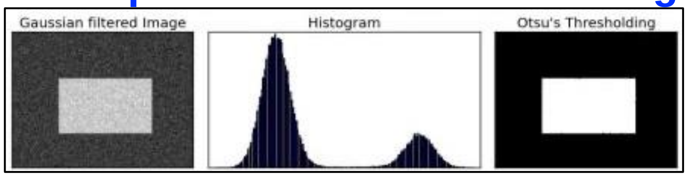
Sphere velocity shot



PDV

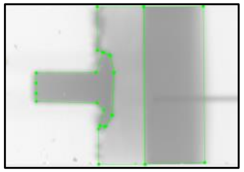
+

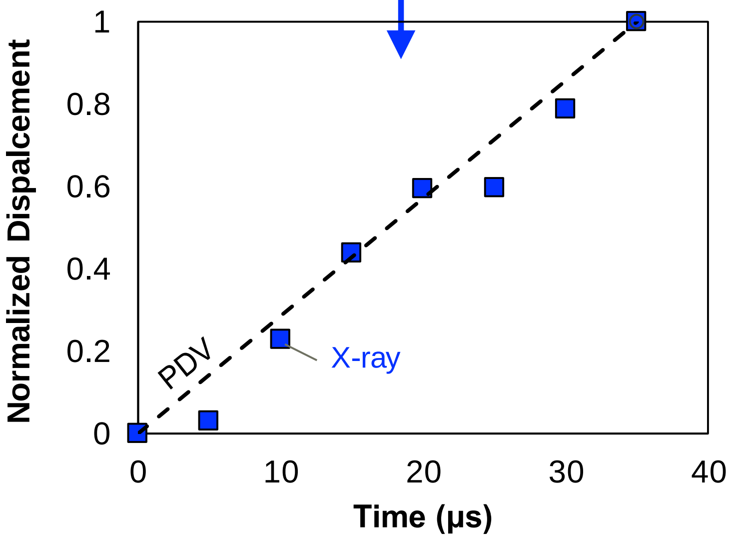
Computer Vision - Thresholding

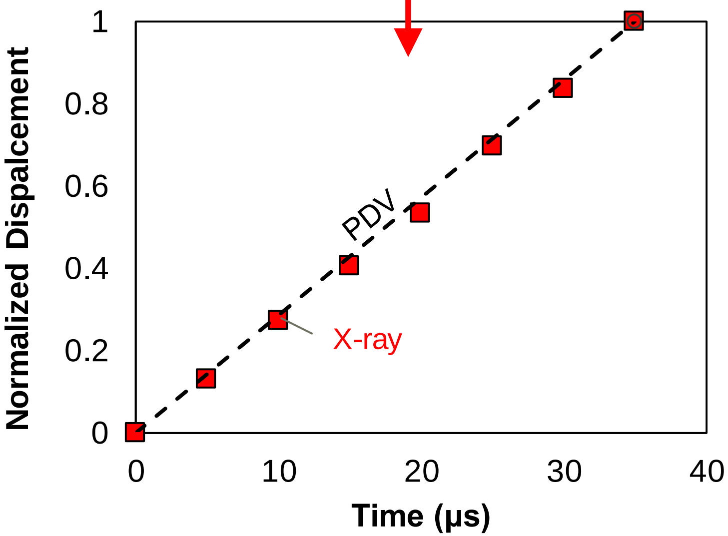


OR….

Machine Learning







- **Initial verification of code functionality for velocity shot (no target)**
  – Track projectile and compute displacement vs time
  – Compare X-ray data to PDV measurements